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14. ABSTRACT
Sparsity-based methods have recently been suggested for tasks such as face and iris recognition. In this project, we evaluated the effectiveness of such methods for automatic target recognition in infrared images. We show how sparsity can be helpful for efficient utilization of data for target recognition. We evaluated the effectiveness of the proposed algorithm in terms of recognition rate and confusion matrices on the well known Comanche forward-looking infrared (FLIR) data set consisting of ten different military targets at different orientations. This

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Report Title

Sparsity-Inspired Recognition of Targets in Infrared Images

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List of papers submitted or published that acknowledge ARO support during this reporting period. List the papers, including journal references, in the following categories:

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Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts): 0

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Number of Manuscripts: 0.00

Patents Submitted

Patents Awarded

Graduate Students

NAME	PERCENT_SUPPORTED
Vishal M Patel	0.50
FTE Equivalent:	**0.50**
Total Number:	**1**

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Rama Chellappa	0.10	No
FTE Equivalent:	**0.10**	
Total Number:	**1**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

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Names of Personnel receiving masters degrees

NAME
Total Number:

Names of personnel receiving PHDs

NAME	
Vishal M Patel	
Total Number:	**1**

Names of other research staff

NAME	PERCENT_SUPPORTED
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Sub Contractors (DD882)

Inventions (DD882)

Sparsity Motivated Automatic Target Recognition

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For Contract W911NF-09-1-0408

Program Manager: Dr. Liyi Dai, ARO.

Statement of the problem studied

Sparsity-based methods have recently been suggested for tasks such as face and iris recognition. In this project, we evaluated the effectiveness of such methods for automatic target recognition in infrared images. We show how sparsity can be helpful for efficient utilization of data for target recognition. We evaluated the effectiveness of the proposed algorithm in terms of recognition rate and confusion matrices on the well known Comanche forward-looking infrared (FLIR) data set consisting of ten different military targets at different orientations. This work was done in collaboration with Dr. Nasser Nasrabadi, Chief Scientist, SEDD, Army research laboratory. This work will be presented at the International Conference on Image Processing being held in Hong Kong in September 2010. A journal paper reporting our work is under preparation.

Summary of the most important results

The objective of an Automatic Target Recognition (ATR) algorithm is to detect and identify each target image into one of a number of classes. The recognition algorithm may consist of several stages. For example, in the first stage a target is detected on the entire image; in the second stage, background clutter is removed; in the third stage, a set of features are computed and finally, in the fourth stage, classification is done by means of a classifier. In this paper, we mainly focus on the last two stages.

Target recognition using forward-looking infrared (FLIR) imagery of different targets in natural scenes is difficult due to high variation in the thermal signatures of targets. Many ATR algorithms have been proposed for FLIR imagery. Wang et al. proposed a modular neural network-based ATR algorithm in [1]. In their algorithm, several neural networks are trained, each optimized for a local region in the image, whose classification decisions are combined to determine the final classification. Wavelet-based vector quantization was used for FLIR ATR in [2] by Chan and Nasrabadi, where a discriminative dictionary was created in the wavelet domain using learning vector quantization. A recognition method based on hidden Markov tree that uses a Karhunen-Loeve representation was proposed by Bharadwaj and Carin in [3]. See [4] for an excellent survey of papers and experimental evaluation of FLIR ATR. The algorithms evaluated in [4] include convolutional neural network (CNN), principal component analysis (PCA), linear discriminant analysis (LDA), learning vector quantization (LVQ), modular neural networks (MNN), and two model-based algorithms, using Hausdorff metric-based matching (H-M) and geometric hashing (G-H).

FLIR images often contain unwanted thermal signatures of the background clutter whose characteristics changes with environment much as change in fog, rain and heat which can make target detection and recognition difficult for automated as well as human observers. Recently, Wright et al. [5] introduced a sparse representation-based classification (SRC) algorithm for face recognition, which was robust to varying expression, illumination, occlusion and disguise and it outperformed many state of the art algorithms. This approach is based on the theories of Compressive Sensing (CS) and Sparse Representation (SR). The idea is to create a dictionary matrix of the training samples as column vectors. The test sample is also represented as a column

vector. Different dimensionality reduction methods are used to reduce the dimension of both the test vector and the vectors in the dictionary. One such approach for dimensionality reduction is random projections [5]. Random projections, using a generated sensing matrix, are taken of both the dictionary matrix and the test sample. It is then simply a matter of solving an $\ell1$ minimization problem in order to obtain the sparse solution. Once the sparse solution is obtained, it can provide information as to which training samples the test vector most closely relates to. Furthermore, it was shown that, if the sparsity of the solution is properly harnessed, the choice of features (e.g. dimensionality reduction method) is no longer critical. The number of features for a given class and the sparse solution become critical.

Motivated by the SRC algorithm, in this effort, we extended the use of SR and CS for the recognition of FLIR target images. In particular, we exploited the inherent block structure of the sparse solution induced by $\ell1$-minimization. Furthermore, our method utilizes a redundant dictionary that includes training data at various azimuth angles, hence achieving orientation invariance. As a result, our algorithm has the ability to identify targets at different orientations. The details of the algorithm are presented in [6, 7]

Experiments

We evaluated our method on the Comanche FLIR data set consisting of different military targets at different orientations. The images are of size 40×75 pixels. In all of our experiments, the dimension of each target image (chip) was reduced from 40×75 to 16×16. There have been a number of approaches suggested for solving block sparsity (BS) promoting optimization problem (15). In our approach, we employed a highly efficient algorithm that is suitable for large scale applications known as the spectral projected gradient (SPGL1) algorithm [8]. The performance of our algorithm is compared with that of several different methods reported in [1], [2], [4]. Our algorithm is also tested using several features, namely PCA features, random projection (RP) features, 2D Haar wavelet features, and downsampled images.

In our data set, there are 10 different vehicle targets. We will denote these targets as TG1, TG2, $\cdot\cdot\cdot$, TG10. For each target, there are 72 orientations, corresponding to the aspect angles of $0^\circ, 5^\circ, \cdot\cdot\cdot$, 355 degrees in azimuth. The range to all the targets is given so that all the target chips are analyzed at 2 kilometers. The data consists of a training set and a test set. We will refer to the training set as the SIG set and test set as the ROI set. The SIG data set has about 13,816 target chips, while there are 3,353 images in the ROI data set. The SIG data set consists of the images that were collected under very favorable conditions. The SIG data set contains 874 to 1468 images per target class spanned over 72 different aspects.

The ROI set consists of only five targets namely TG1, TG2, TG3, TG4 and TG7. The target images for the ROI set were taken under less favorable conditions, such as targets with different weather conditions, in different background, in and around clutter; hence, this data is very challenging. There are 577 to 798 images for each of these five target classes. All the images in the SIG and ROI sets were normalized to a fixed range with the target put approximately in the center. The orientation in the ROI set was given very coarsely; every 45degrees.

In the first set of experiments, the training and test images were chosen from the SIG data set.

For training, we randomly choose 11 target chips for each target per aspect angle, called TRAINSIG. Since we have a total of 72 aspects (e.g. $0^\circ, 5^\circ, \cdots, 355$ degrees) for each target, we used a total of $11\times72 = 792$ targets per class. The probabilities of correct classification for these experiments are 98.48%, 99.18%, 99.96% and 99.95% for the downsampled, RP, PCA and Haar wavelet features, respectively. All the features performed approximately the same for these experiments.

In the second set of experiments, we again randomly selected 11 targets per aspect angle from the SIG data set for training. Again, the resulting dictionary A is of size 256×7290. We randomly selected 1000 images from the ROI set for testing, called the TEST-ROI set. We extracted various features and applied our BS-based algorithm on these features as was done for the TRAINSIG dataset. The probabilities of correct classification for these experiments are 75.10, 76.30, 78.89 and 76.45% for the downsampled, RP, PCA and Haar wavelet features, respectively. Again, PCA features gave the best performance. In these experiments, the TEST-ROI set contained only five targets, but all of the outputs were active.

The best recognition results on the TEST-SIG and TEST-ROI data sets were obtained by using the PCA features. Our method achieves recognition rates of 99.96% and 78.89% on TEST-SIG and TEST-ROI, respectively and it outperforms the other methods such as CNN, MNN, PCA, LVQ, LDA, H-M and G-H [1], [2], [4]. Also, note that our method is more general than the competing methods presented in [1] and [2]. In their methods, to deal with the background artifacts, they use several rectangular windows of different size based on the ground truth silhouette computer-aided design models. As a result, their performance significantly depends on the choice of windows. In contrast, the method presented here does not require any windowing or prior knowledge about the size of the targets.

Summary and conclusions

We have developed a framework for ATR using the theory of sparse representations and compressive sensing. This entails solving a block-sparsity promoting optimization problem on various features. Various experiments on the Comanche FLIR data set have shown promising results. Several future directions of inquiry are possible considering our new approach to ATR. For instance, instead of using the ℓ_1 minimization one can consider greedy pursuits such as orthogonal matching pursuit and CoSaMP [9], [10], [11]. Greedy pursuits are known to converge much faster than the optimization based methods and have the same theoretical guarantees as some of the optimization based methods. Note that the sparsity motivated methods for ATR presented here for FLIR images can be easily extended to the other ATR problems such as the one based on synthetic aperture radar imagery.

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